

A method combining temporal causality with multi-scale spatiotemporal feature encoding for sea ice concentration forecasting

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model’s ability to capture spatiotemporal features. We integrated sea ice concentration data from the US National Snow and Ice Data Centre (NSIDC) with atmospheric -ocean multivariates. Through comparative experiments and comprehensive analysis, we demonstrate that STICNet exhibits excellent numerical fit and spatiotemporal consistency across forecast lead times ranging from 1 to 6 months, significantly improving the model’s ability to characterise sea ice boundaries during the critical transition periods of spring melt and autumn freeze.

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1 Introduction

The Arctic region is experiencing significant climate warming, with rates of warming reaching two to four times the global average; [Serreze and Barry \(2011\)](#); [Screen and Simmonds \(2010\)](#) characterized this phenomenon as the Arctic amplification effect. This has led to a rapid decline in Arctic sea ice, both in extent and concentration. [Heuzé and Jahn \(2024\)](#); [Cavallo et al. \(2025\)](#); [Stroeve et al. \(2025\)](#) showed that these impacts are felt across a wide range of scales, from the global climate system to regional socio-economic contexts. Among these, sea ice concentration (SIC) forecasting is one of the core tasks of polar climate research. The objective of this task is to infer the distribution and density of sea ice over a specific future period or time series, based on historical observational data and climatic background information. By modelling the temporal dynamics of SIC, it is possible to proactively identify ice edge advance trajectories, the rate of ice retreat, and anomalous melting events. This is not only of direct significance for the conservation of polar ecosystems and resource development, but also, as reviewed by [Guemas et al. \(2016\)](#), provides a vital foundation for shipping route planning and vessel navigation. Spatio-temporal anomalies in SIC are also closely linked to adjustments in the global energy balance and play a systemic role, particularly in influencing polar albedo, surface radiation balance and climate

feedback mechanisms. Consequently, sea ice concentration forecasting is a vital tool for studying trends in polar sea ice evolution and climate response mechanisms.

Due to its complex nonlinear dynamic characteristics, the dynamic prediction of sea ice concentration has long been a challenge in climate science. Numerous methods have been proposed for dynamically forecasting sea ice concentration. These include statistical modeling approaches utilizing historical climate data and mathematical models, as well as numerical modeling methods simulating physical processes within the ocean-atmosphere system. Despite significant progress made with these methods, limitations persist at longer spatial and temporal scales. This is primarily because statistical models struggle to capture intricate nonlinear relationships, while model-based forecasting methods heavily depend on initial sea ice conditions and introduce uncertainties during simulation. Particularly against the backdrop of global warming driving the Arctic climate system into a non-steady state, the breakdown of historical statistical relationships and the emergence of systematic model biases become increasingly pronounced. This further complicates the achievement of high-precision, high-confidence predictions.

Currently, deep learning techniques demonstrate significant potential in sea ice forecasting. Their core principle involves automatically extracting spatio-temporal features from sea ice evolution and learning the complex nonlinear spatio-temporal patterns within the sea ice system.

He et al. (2025) developed the SR-SICFormer model, a Transformer encoder-decoder framework that integrates super-resolution reconstruction with spatio-temporal feature learning. By introducing a direct prediction strategy and spatio-temporal attention mechanism, it effectively avoids the error accumulation issue in recursive prediction, enabling efficient long-term forecasting. Additionally, they designed a 3D U-Net unit tailored for spatio-temporal sequences, achieving end-to-end high-resolution prediction. Experiments demonstrate that SR-SICFormer achieves

84 outstanding performance in 15-day forecasting tasks, with an *RMSE* of 0.0504 and
85 a correlation coefficient of 0.9420, significantly outperforming traditional models. In
86 60-day subseasonal forecasting, its *RMSE* remained below 0.065, demonstrating par-
87 ticularly robust predictive capability and generalization during the ice-melt season.
88 This validates the model’s effectiveness and advanced nature for high-resolution,
89 long-term sea ice forecasting.

90 Gousseau et al. (2025) proposed a novel graph neural network model named
91 GraphSIFNet, which employs a graph long short-term memory network within a
92 sequence-to-sequence architecture for sea ice forecasting. This approach enables the
93 discretization of the study area into an irregular grid, achieving higher spatial resolu-
94 tion near coastlines to more explicitly model spatial relationships. The model employs
95 attention-based graph transformer convolutions to enhance interpretability regard-
96 ing information flow directions. It innovatively incorporates climate state as decoder
97 input to aid learning deviations from normal conditions. Experimental results demon-
98 strate that over a 90-day forecast period in Hudson Bay, the model reduces root mean
99 square error by up to 10% compared to statistical benchmarks (linear combinations
100 of persistence and climate state) for short-to-medium-term sea ice concentration fore-
101 casts (particularly during the melt season). For long-term sea ice presence forecasts, it
102 maintains approximately 10% accuracy improvement even at 90 days lead time, and
103 outperforms the ECMWF’s sub-seasonal to seasonal forecasting system during the
104 melt season.

105 Qin et al. (2025) proposed an innovative deep learning model named WaveletNet.
106 By deeply integrating wavelet transforms into the network architecture, it constructs
107 unique spatial and temporal wavelet modules. The spatial module employs a parallel
108 branch design combining local CNNs with global wavelet transforms, effectively fus-
109 ing local details and global spatial features of sea ice. The temporal module precisely

110 captures the cross-scale temporal dependencies of sea ice changes through multi-
 111 scale convolutions and cascaded wavelet computational units. Experimental validation
 112 demonstrates that across prediction horizons ranging from 1 to 12 months, Wavelet-
 113 Net comprehensively outperforms traditional comparison models such as U-Net and
 114 ConvLSTM in both $RMSE$ and R^2 evaluation metrics. It exhibits particularly out-
 115 standing performance in long-term forecasting tasks exceeding 5 months and effectively
 116 mitigates the performance degradation caused by the spring predictability barrier. [Ali](#)
 117 [and Wang \(2022\)](#) proposed a U-Net-based spatial and multi-temporal deep learning
 118 model. Utilizing an encoder-decoder architecture with skip connections, it processes
 119 multi-temporal input streams to reconstruct spatial distributions of sea ice at future
 120 time steps. This model reduced pixel-wise SIC prediction errors for 6-month forecasts
 121 by 60% compared to state-of-the-art models. However, existing methods still lack the
 122 ability to synergistically fuse multi-temporal scale data.

123 To address the aforementioned challenges, we propose a sequence modeling-based
 124 U-Net Arctic sea ice concentration prediction model. The encoder utilizes parallel
 125 branches to extract spatio-temporal features from multi-temporal resolution inputs,
 126 while cross-layer connections propagate shallow features. The decoder regenerates the
 127 spatial distribution of SIC at future time steps through upsampling, skip connec-
 128 tions, and multi-temporal data. Its core advantage lies in efficiently capturing complex
 129 spatio-temporal dynamics by combining multi-timescale feature extraction with time-
 130 gated long-term sequence modeling, integrated through cross-layer attention fusion.
 131 Our contributions are summarized as follows:

- 132 • By adopting a temporal causal convolution and transposed convolution encoding-
 133 decoding mechanism that strictly adheres to the physical unidirectional flow of time,
 134 the method effectively avoids the issue of inflated predictions caused by leakage
 135 of future information, thereby ensuring the physical validity and reliability of the
 136 prediction results.

- 137 • A multi-scale spatiotemporal feature hierarchical encoding and decoding structure
138 has been designed to address the challenge of characterising complex evolution
139 where local abrupt changes in sea ice concentration coexist with global gradual
140 changes, and short-term fluctuations overlap with long-term trends, thereby signif-
141 icantly enhancing our understanding of key processes such as marginal melting and
142 the retreat of multi-year ice.
- 143 • A multi dimensional attention mechanism is integrated into the skip connections to
144 further refine the model’s ability to capture spatio-temporal features. This optimizes
145 the feature fusion process by adaptively emphasizing important feature channels
146 and spatial locations.

147 The remainder of the paper is organized as follows: Section 2 offers a compre-
148 hensive review of related methods in sea ice prediction. In Section 3, we provided
149 a detailed introduction to the overall architecture and components of the proposed
150 model. Section 4 presents experimental results along with detailed analysis. Finally,
151 Section 5 concludes our study.

152 2 Related work

153 Sea ice forecasting is of great importance for addressing issues relating to polar ship-
154 ping safety, marine ecological conservation and global climate regulation. Researchers
155 are studying sea ice events from the perspectives of polar climate data analysis,
156 the mechanisms of atmosphere-sea ice-ocean interactions, and seasonal and interan-
157 nual variations in sea ice, with a view to improving forecasting accuracy. Current
158 research into sea ice forecasting can be categorised into three types: numerical
159 dynamical models, statistical models and deep learning models. These approaches
160 enhance the capability and efficiency of sea ice forecasting from different perspectives,
161 namely physical mechanisms, statistical patterns and the learning of spatio-temporal
162 characteristics, respectively.

2.1 Sea ice prediction based on numerical models

Numerical modeling approaches rely on physical laws to predict sea ice changes by describing thermodynamic processes within specific dynamic frameworks and under specified initial and boundary conditions.

[Yang et al. \(2014\)](#) developed a sea ice-ocean coupled model based on MITgcm, employing a localized SEIK filter to jointly assimilate SMOS-inverted sea ice thickness with SSMIS sea ice concentration data for winter Arctic sea ice forecasting. This approach integrates physically driven mechanisms with satellite observations, enhancing the accuracy of model initial conditions and strengthening the predictive capability of the dynamic model. [Wang et al. \(2013\)](#) employed a fully coupled atmosphere-ocean-sea ice model (CFSv2), identifying initial sea ice thickness and atmospheric circulation anomalies as critical factors affecting the accuracy of interannual sea ice variability predictions. They demonstrated its utility in seasonal forecasts of the Sea Ice Extent (SIE) in the Arctic. [Bushuk et al. \(2017\)](#) similarly developed an atmospheric-ocean-sea ice model, demonstrating that detrend regional SIE forecasts exhibit skill up to 11 months lead time. [Zhang \(2021\)](#) investigated consistency issues in key sea ice properties-thickness, concentration, and motion-across 6 km, 4 km, and 2 km horizontal resolutions using the high-resolution HIOMAS sea ice-ocean coupled model. The study found that without parameter adjustments, models at different resolutions produced highly consistent simulations of large-scale sea ice properties, indicating that commonly used VP constitutive relationships and strength parameters are transferable across multi-scale models. [Adcroft et al. \(2019\)](#) systematically introduced the GFDL-developed global ocean-sea ice model OM4.0, widely applied in ocean circulation simulations and sea ice evolution studies. The model employs the MOM6 dynamic core and SIS2 sea ice module, featuring hybrid vertical coordinates, multiscale parameterization, and high-resolution grids to support detailed characterization of sea ice processes in mid-to-high latitudes. While physically based numerical models offer

190 good interpretability and can describe dynamic sea ice changes, challenges remain in
191 real-time and lightweight applications.

192 **2.2 Statistical sea ice forecasting**

193 Statistical modeling approaches, as demonstrated by [Drobot \(2007\)](#), construct statis-
194 tical models of sea ice variables over time or in response to characteristic variables by
195 establishing mappings between sea ice, atmospheric, and oceanic variables, thereby
196 predicting future sea ice extent.

197 [Wang et al. \(2016\)](#) developed a statistical method based on vector autoregressive
198 models to forecast interseasonal variations in summer Arctic sea ice concentration.
199 Relying solely on historical sea ice concentration data, this model significantly outper-
200 formed anomaly persistence and damped anomaly persistence methods over 20-60-day
201 prediction horizons across the pan-Arctic region, particularly in marginal seas like
202 the Barents and Kara Seas. [Yuan et al. \(2016\)](#) proposed an Arctic sea ice forecasting
203 method based on a linear Markov model. By utilizing multivariate empirical orthog-
204 onal functions to construct a low-dimensional space for the atmosphere-ocean-sea ice
205 coupled system, they achieved monthly forecasts of seasonal sea ice concentration
206 across the entire Arctic region. This model demonstrates high predictive capability
207 across multiple marginal seas, outperforming anomaly persistence and climate field ref-
208 erence models at multiple seasonal scales, and exhibits strong pan-regional predictive
209 potential without relying on dynamic models. [Wang et al. \(2019\)](#) employed multivari-
210 ate empirical orthogonal functions and linear Markov models to statistically capture
211 the covariance relationships within the sea ice-ocean-atmosphere system for predict-
212 ing future sea ice thickness. Experimental results indicate optimal model performance
213 at 12 months lead time, achieving anomaly correlation coefficients ranging from 0.7
214 to 0.8. [Horvath et al. \(2020\)](#) propose a Bayesian logistic regression framework for
215 probabilistic forecasting of September Arctic sea ice minimum. Experimental results

216 indicate superior performance over climatological and anomaly persistence baselines
217 across all delivery periods. Compared to numerical modeling approaches, statistical
218 methods offer lightweight advantages such as structural simplicity and high inference
219 efficiency. However, their modeling capabilities for nonlinear processes and complex
220 spatiotemporal coupling remain limited, with notable shortcomings in long-term and
221 rapidly changing scenarios.

222 2.3 Deep learning-based sea ice prediction

223 Deep learning methods can automatically extract spatio-temporal features in sea ice
224 evolution, possess robust nonlinear modeling capabilities, adapt to large-scale obser-
225 vational data, and enable end-to-end prediction workflows. Compared to traditional
226 methods, they demonstrate superior generalization capabilities and computational
227 efficiency under multi-region and multi-time-series conditions.

228 As demonstrated by [Bilgili et al. \(2025\)](#); [Zhang et al. \(2023\)](#); [Al-Selwi et al. \(2024\)](#),
229 Recurrent Neural Networks (RNNs) excel at processing time series data, capturing
230 temporal dependencies within input sequences, making them suitable for modeling
231 temporal trends in sea ice. Their structure retains historical information, offering
232 strong adaptability for constructing short- or medium-term sea ice prediction mod-
233 els with predictive depth. [Choi et al. \(2019\)](#) proposed an artificial neural network
234 model combining a gated recurrent unit encoder with a feedforward neural network
235 decoder to achieve short-term frame-by-frame predictions of Arctic sea ice concentra-
236 tion. This approach incorporates global information, including statistics such as sea
237 ice extent, distribution center, and spatial dispersion, to compensate for the lack of
238 spatial correlation caused by cell-by-cell independent predictions, thereby enhancing
239 overall forecasting accuracy. [Gao et al. \(2025\)](#) proposed a hybrid model combin-
240 ing WGAN, which leverages data generation capabilities, and LSTM, which excels
241 in temporal forecasting, for single-step sea ice thickness prediction. Experimental

242 results demonstrate that compared to traditional LSTM models, the WGAN-LSTM
243 model achieves comprehensive performance improvements of 51.9% and 75.2% in
244 MSE and DISO, respectively, using these loss functions. [Chi and Kim \(2017\)](#) pro-
245 posed a fully observation-image-data-driven deep neural network approach utilizing
246 multilayer perceptrons and LSTMs for monthly-scale Arctic sea ice concentration
247 forecasting. This method requires no physical variables, relying solely on passive
248 microwave remote sensing data as input to construct a supervised learning frame-
249 work. It achieves both short-term and long-term predictions, with results surpassing
250 traditional autoregressive models in both accuracy and image structural consistency.
251 This demonstrates the potential of fully data-driven deep learning for long-term
252 sequence modeling and lightweight sea ice forecasting. [Wei et al. \(2022\)](#) proposed
253 an attention-based LSTM model for monthly-to-subseasonal sea ice concentration
254 forecasting across the pan-Arctic region. This approach incorporates multiple enhance-
255 ments, including a composite loss function and temporal attention modules, to fully
256 leverage SIC sequence information from the preceding 12 months. Results demonstrate
257 superior prediction accuracy compared to conventional LSTMs, empirical methods,
258 and selected numerical models. [Ali et al. \(2021\)](#) propose an attention-based ensem-
259 ble LSTM model, EA-LSTM, for predicting monthly Arctic sea ice extent (SIT). This
260 approach integrates multi-temporal resolution LSTM models at daily and monthly
261 scales, employing attention mechanisms to weight learning across different tempo-
262 ral granularities, thereby enhancing multi-source information modeling capabilities.
263 Experimental results demonstrate superior performance compared to various tradi-
264 tional machine learning methods and existing deep learning architectures, particularly
265 during the summer melt season.

266 [Xiao et al. \(2019\)](#); [Dong et al. \(2024\)](#) demonstrated that ConvLSTM possesses the
267 capability to simultaneously model spatial structure and temporal dynamics in fore-
268 casting, making it particularly well-suited for handling sequential data with strong

269 spatiotemporal coupling characteristics, such as remote sensing imagery. Compared
 270 to traditional time series models, it demonstrates greater stability and accuracy in
 271 capturing sea ice edge changes and performing multi-step continuous predictions.
 272 [Zhang et al. \(2022\)](#) proposed a deep learning model, ConvLSTM-CRF, integrating
 273 ConvLSTM with a dense conditional random field (CRF) to forecast monthly sea
 274 ice concentration in the Arctic. This approach retains temporal modeling capabilities
 275 while incorporating CRF to enhance spatial context modeling, significantly improv-
 276 ing prediction performance in marginal regions and seasons with abrupt changes. It
 277 demonstrates the potential of deep models in extracting fine-grained spatial structures.
 278 [Liu et al. \(2021a\)](#) proposed a ConvLSTM-based deep learning model for daily-scale
 279 Arctic sea ice concentration prediction. This approach fully integrates the spatial
 280 modeling capability of convolutional operations with the temporal dependency mod-
 281 eling capability of LSTM networks, effectively capturing the spatiotemporal variation
 282 characteristics of SIC. It significantly outperforms traditional CNN methods, partic-
 283 ularly for short-term sea ice condition forecasting in shipping-sensitive regions like
 284 the Northeast Passage. [Kim et al. \(2021\)](#) proposed a multi-task deep learning model
 285 integrating CNN and ConvLSTM architectures to simultaneously predict Arctic sea
 286 ice concentration and extent. This approach learns spatio-temporal features through
 287 shared network structures and introduces a custom loss function to address land
 288 masking issues, achieving collaborative optimization of both variables. Experimen-
 289 tal results demonstrate that compared to single-task models, this multi-task model
 290 exhibits higher accuracy and generalization capability in monthly-scale sea ice predic-
 291 tion. [Chi et al. \(2021\)](#) proposed a Two-Stream ConvLSTM model based on perceptual
 292 loss functions for sequence-to-sequence prediction of Arctic sea ice concentration. This
 293 approach designs parallel sparse and detail learning channels, combines convolutional
 294 structures to extract multi-scale features, and incorporates a VGG-based perceptual
 295 loss function to enhance spatial structural consistency in predicted images. Compared

296 to traditional LSTMs and single ConvLSTM models, this architecture demonstrates
297 greater stability in multi-step forecasting and more effectively captures the spatiotem-
298 poral dynamics of sea ice evolution. [Liu et al. \(2021b\)](#) proposed a deep learning model
299 based on multi-factor inputs, integrating an enhanced PredRNN++ network with a
300 gradient loss function to achieve continuous daily-scale predictions of Arctic sea ice
301 concentration for up to 9 days. This approach not only comprehensively models the
302 spatiotemporal variations of SIC but also optimizes the spatial structural similarity of
303 prediction results by incorporating local gradient information, demonstrating strong
304 applicability in sensitive regions such as the Northeast Passage.

305 The U-Net architecture has been validated in numerous remote sensing and image
306 segmentation tasks due to its exceptional spatial detail extraction and pixel-level pre-
307 diction capabilities [Ma et al. \(2025\)](#); [Huang et al. \(2022\)](#). Its unique encoder-decoder
308 structure and skip connections effectively preserve and restore high-resolution spatial
309 information, which is crucial for accurately predicting sea ice edge lines and mor-
310 phological changes. Grigoryev et al. proposed a lightweight deep learning approach
311 based on the U-Net architecture for achieving daily-scale short-term sea ice concen-
312 tration forecasts in Arctic regions such as the Barents Sea, Labrador Sea, and Laptev
313 Sea [Grigoryev et al. \(2022\)](#). This approach utilizes JAXA AMSR2 remote sensing
314 data and GFS weather elements to construct a high-resolution dataset suitable for
315 real-time operations. By training models through two direct and recursive forecasting
316 modes, it achieves continuous sea ice forecasts up to 10 days, significantly outper-
317 forming persistence and trend-based baselines. [Ren et al. \(2022\)](#) introduced SICNet,
318 a fully convolutional deep learning model for daily sea ice concentration forecasting
319 across the pan-Arctic region during the summer melt season. Employing an encoder-
320 decoder architecture with a spatio-temporal attention module to enhance multi-scale
321 spatio-temporal dependency modeling, SICNet performs end-to-end predictions solely

322 based on historical SIC sequences, offering high accuracy and lightweight advan-
 323 tages. Experiments demonstrate that SICNet achieves significant improvements in
 324 accuracy and stability compared to traditional CNN and LSTM models, exhibiting
 325 particularly strong robustness in 28-day advance predictions of extreme minimum sea
 326 ice events. [Andersson et al. \(2021\)](#) proposed a probabilistic deep learning forecast-
 327 ing system named IceNet, built upon a U-Net convolutional architecture to generate
 328 monthly probability distributions of sea ice concentration for the next six months.
 329 This method employs transfer learning using CMIP6 climate simulation data and
 330 observational records, incorporating uncertainty estimation and boundary region iden-
 331 tification mechanisms. It significantly outperforms mainstream dynamic models in
 332 seasonal-scale predictions of extreme sea ice events, demonstrating the accuracy and
 333 generalization advantages of deep learning in pan-Arctic seasonal forecasting tasks.

334 **3 Method**

335 The proposed framework is illustrated in Fig. 1, with its core being a U-Net archi-
 336 tecture based on an enhanced encoder-decoder structure. This model employs a
 337 dual-parallel branch (stage1, stage2) and a supplementary branch (stage3) structure.
 338 Stage1 and stage2 capture seasonal trends and sub-seasonal fluctuations in sea ice,
 339 while stage3 supplements global features to constrain overall evolutionary patterns.
 340 Input data first undergoes preliminary spatio-temporal feature extraction via ConvL-
 341 STM, capturing fundamental dependencies such as short-term ice margin dynamics
 342 during the melt season to anchor core information for the encoding phase. The encod-
 343 ing phase processes features sequentially through three core modules: Temporal causal
 344 convolutional encode (TCCE) establishes temporal unidirectionality constraints to
 345 prevent leakage of future information, ensuring physical plausibility for seasonal-scale
 346 predictions. Spatial temporal encode block (STEB) integrates local ice margin dynam-
 347 ics with global ice sheet trends to precisely locate critical regions like interglacial lakes.

348 a multi-dimensional attention mechanism highlights key variables through feature
 349 weighting, correcting prediction biases for extreme melt events. This stage com-
 350 bines subsampling to compress dimensionality while preserving essential features, and
 351 employs skip connections to transmit shallow-layer details to the decoding phase. The
 352 decoding stage employs temporal transposed convolution decode (TTCD) to restore
 353 temporal scales, preventing prediction discontinuities in long-term sequences. Spatial
 354 temporal decode block (STDB) reconstructs pixel-level sea ice distribution. And the
 355 multi-dimensional attention mechanism further corrects errors in marginal regions.
 356 After upsampling, the final output is a spatial distribution map of pixel-level sea ice
 357 concentration for the next 1-6 months.

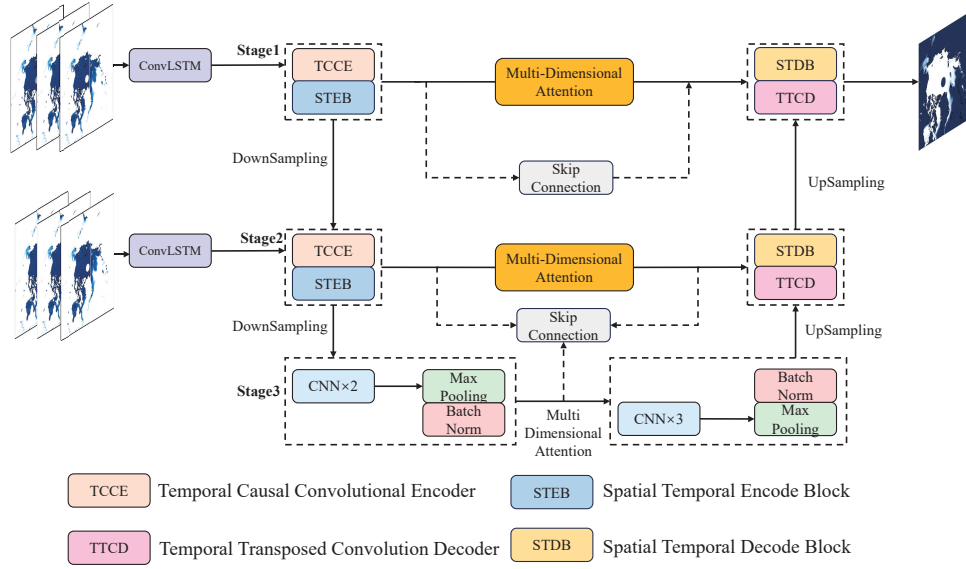


Fig. 1 Overall framework of the STICEnet model

3.1 Time-domain encoding and decoding coordination mechanism (TEDCM)

To enhance the model’s ability to capture temporal features in sea ice time series, a temporal encoding and decoding coordination mechanism was developed, as illustrated in Fig. 2. TCCE employs causal convolution layers to establish temporal causal constraints, strictly adhering to the unidirectional temporal nature of physical processes when extracting dynamic features such as sea ice coverage. This prevents reverse interference from future information during the melting period. TTCD performs spatio-temporal feature reconstruction, restoring temporal features to their original time scale while preventing over-utilization of features through a gating mechanism. TCCE and TTCD are integrated into the encoder and decoder components respectively, thereby enhancing the model’s processing capability for sea ice temporal characteristics. The two modules process sea ice spatiotemporal features through an encoder-decoder architecture, thereby improving the model’s ability to capture sea ice evolution patterns.

Given an input feature $A_\alpha \in \mathbb{R}^{C_{i\alpha} \times N \times T_{i\alpha} \times H}$, where $C_{i\alpha}$ denotes the channel dimension of the input, N represents the number of nodes, and $T_{i\alpha}$ signifies the temporal dimension of the input. In the temporal causal constraint stage of TCCE, the input features A_α undergo a convolution operation to obtain foundational temporal features that depend solely on historical time-step information:

$$CausConv(\mathbf{A}_\alpha) = \mathbf{A}_\alpha \Theta_{\alpha c} + \gamma_{\alpha c} \quad (1)$$

where $CausConv(\mathbf{A}_\alpha)$ denotes the causal convolution encoding temporal features, and $\Theta_{\alpha c}$ and $\gamma_{\alpha c}$ are the weight and bias parameters of the convolution.

Second, gated linear units are employed to fuse causal convolutional features through gating. By calculating feature importance weights, the representation of

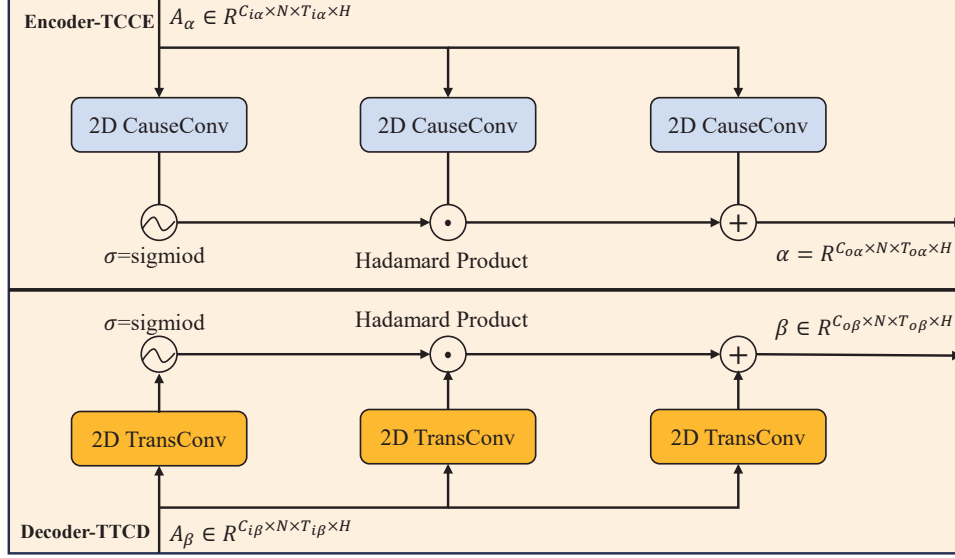


Fig. 2 Time-domain encoding and decoding coordination mechanism

critical temporal nodes in de-icing and icing processes is enhanced:

$$g(\mathbf{A}_\alpha) = \sigma(\mathbf{A}_\alpha \mathbf{\Theta}_{\alpha g} + \gamma_{\alpha g}) \quad (2)$$

here, $g(\mathbf{A}_\alpha)$ represents the gating function controlling the output of the causal convolution, σ is the Sigmoid activation function, and $\mathbf{\Theta}_{\alpha g}$ and $\gamma_{\alpha g}$ are the parameters of the gate.

Feature transfer and adaptation are performed on input feature $\mathbf{A}_\alpha$ using residual connections to prevent information loss during feature extraction, thereby obtaining raw feature information that can be directly transferred:

$$r(\mathbf{A}_\alpha) = \mathbf{A}_\alpha \mathbf{\Theta}_{\alpha r} + \gamma_{\alpha r} \quad (3)$$

where $\mathbf{\Theta}_{\alpha r}$ and $\gamma_{\alpha r}$ are the weight and bias parameters of the residual projection.

390 Finally, the filtered features and residual features are integrated and nonlinearly
 391 transformed using the ReLU activation function to obtain the final encoded output of
 392 TCCE:

$$\alpha = \eta(CausConv(\mathbf{A}_\alpha) \odot g(\mathbf{A}_\alpha) + r(\mathbf{A}_\alpha)) \quad (4)$$

393 here, η denotes the ReLU function, and $\odot$ represents element-wise Hadamard product.

394 The Temporal Transposed Convolution Decode(TTCD) is designed to restore the
 395 original temporal resolution of sea ice time series and generate enriched temporal
 396 features during decoding. It comprises transposed convolutions, batch normaliza-
 397 tion, and max-pooling layers to reconstruct temporal scales. Given an input $\mathbf{A}_\beta \in$
 398 $\mathbb{R}^{C_{i\beta} \times N \times T_{i\beta} \times H}$, where $C_{i\beta}$ is the input channel dimension and $T_{i\beta}$ is the input
 399 temporal dimension, The TTCD is implemented as shown in Eq. 5 to 8:

$$\beta = \eta(TransConv(\mathbf{A}_\beta) \odot g(\mathbf{A}_\beta) + r(\mathbf{A}_\beta)) \quad (5)$$

400

$$TransConv(\mathbf{A}_\beta) = \mathbf{A}_\beta \Theta_{\beta c} + \gamma_{\beta c} \quad (6)$$

401

$$g(\mathbf{A}_\beta) = \sigma(\mathbf{A}_\beta \Theta_{\beta g} + \gamma_{\beta g}) \quad (7)$$

402

$$r(\mathbf{A}_\beta) = \mathbf{A}_\beta \Theta_{\beta r} + \gamma_{\beta r} \quad (8)$$

403 where $TransConv(\mathbf{A}_\beta)$ denotes a 1D transposed convolution operation for decoding
 404 temporal features, with $\Theta_{\beta c}$ and $\gamma_{\beta c}$ representing its kernel weights and bias param-
 405 eters, respectively. The function $g(\mathbf{A}_\beta)$ acts as a gating mechanism that adaptively
 406 modulates the output of the transposed convolution, parameterized by $\Theta_{\beta g}$ and $\gamma_{\beta g}$.
 407 The residual connection $r(\mathbf{A}_\beta)$, with parameters $\Theta_{\beta r}$ and $\gamma_{\beta r}$, is introduced to alle-
 408 viate network degradation and facilitate gradient flow during training. The output of
 409 the TTCD module is denoted as $\beta = \mathbb{R}^{C_{o\beta} \times N \times T_{o\beta} \times H}$, where $C_{o\beta}$ indicates the out-
 410 put channel dimension and $T_{o\beta}$ corresponds to the output temporal dimension. The

ReLU activation function is represented by η , σ refers to the Sigmoid function, and $\odot$ signifies the element-wise Hadamard product.

3.2 Multi-Scale spatiotemporal feature encoding and decoding of sea ice evolution (MSFED)

In sea ice forecasting tasks, accurately modeling the spatial variation and temporal evolution of sea ice is crucial. Due to the complexity of sea ice coverage areas, it is often necessary to comprehensively consider spatiotemporal features across different time scales in sea ice prediction. To effectively capture these features, this section proposes a spatiotemporal feature extraction structure based on Mamba. As shown in Fig. 3, this architecture comprises two primary modules: the STEB and the STDB. These modules respectively extract spatio-temporal features from multidimensional sea ice data and reconstruct sea ice concentration maps, thereby enhancing the modeling capability for sea ice concentration variations.

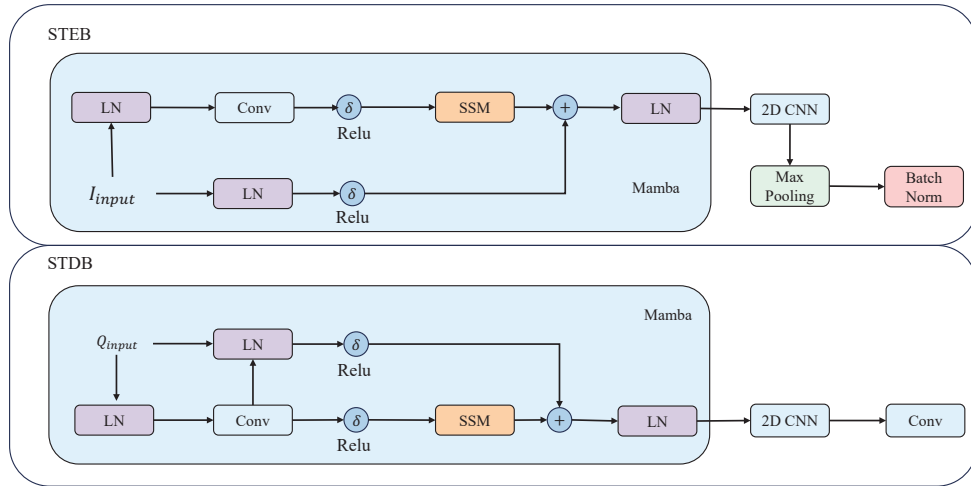


Fig. 3 Schematic diagram of multi-scale spatiotemporal feature encoding-decoding module

424 The STEB module is responsible for extracting spatiotemporal features from the
 425 input multi-dimensional sea ice data, which typically includes monthly and bi-monthly
 426 sea ice concentration maps possessing both spatial structure and temporal dynam-
 427 ics. The STEB module first employs multi-level convolutional operations and pooling
 428 layers to capture spatial features, followed by a Mamba module to model dynamic
 429 temporal dependencies across sequences. The STDB module decodes and reconstructs
 430 the spatiotemporal features extracted by the encoder to produce the final sea ice con-
 431 centration prediction map. During decoding, the model performs upsampling on the
 432 features derived from STEB, followed by a series of convolutional operations to pro-
 433 gressively restore spatial and temporal details. Both STEB and STDB are embedded
 434 into the encoder and decoder paths of a U-Net architecture. Specifically, the encoder
 435 enhances the input tensor $\mathbf{I}_{input} \in \mathbb{R}^{T \times W \times H \times C}$ by unfolding it along the time dimen-
 436 sion into sequences. These sequences are processed by the Mamba module and then
 437 reconstructed into spatial feature maps. The temporal unidirectional collaborative
 438 module serves as the input sequence to the Mamba block, implemented as follows:
 439 First, the input features are normalized to stabilize the training process:

$$\mathbf{Z}_1 = \text{Linear}(\mathbf{I}_{input}) \quad (9)$$

440 Next, a 2D convolution is applied to extract local spatio-temporal patterns,
 441 followed by an activation function to enhance representational capacity:

$$\mathbf{Z}_2 = \delta(\text{Conv2D}(\mathbf{Z}_1, \mathbf{W}_{conv})) \quad (10)$$

442 The resulting features $\mathbf{Z}_2$ are then processed through a state-space model to cap-
 443 ture dynamic temporal evolution. A classical linear state-space structure is adopted,

444 incorporating hidden state variables to model long-range dependencies across time
 445 steps and strengthen the model’s ability to learn internal temporal patterns.

446 Firstly, flatten the spatial feature maps at each time step. Specifically, for the
 447 input feature tensor $\mathbf{Z}_2 \in \mathbb{R}^{T \times W \times H \times C}$, each frame $\mathbf{Z}_2[t]$ is flattened into a vector
 448 $\mathbf{k}_t \in \mathbb{R}^{W \times H \times C}$, forming a temporal feature sequence:

$$\mathbf{k}_t = \text{Flatten}(\mathbf{Z}_2[t]), \quad t = 1, 2, \dots, T \quad (11)$$

449 Subsequently, the dynamic update process of the state-space model (SSM) is intro-
 450 duced. The hidden state $\mathbf{h}_t$, which represents long-term memory, is updated based on
 451 the previous state and the current input $\mathbf{k}_t$:

$$\mathbf{h}_t = M\mathbf{h}_{t-1} + N\mathbf{k}_t \quad (12)$$

452

$$\mathbf{y}_t = Z\mathbf{h}_t \quad (13)$$

453 here, $\mathbf{k}_t$ denotes the input feature at time step t , $\mathbf{h}_t$ is the hidden state, and $\mathbf{y}_t$ is the
 454 output for the current time step.

455 Finally, the outputs from all time steps $\{\mathbf{y}_1, \mathbf{y}_2, \dots, \mathbf{y}_t\}$ are concatenated along
 456 the temporal dimension to form a unified dynamic feature representation:

$$\mathbf{Z}_3 = \text{Concat}([\mathbf{y}_1, \mathbf{y}_2, \dots, \mathbf{y}_t]) \quad (14)$$

457 To enhance the completeness of feature representation while preserving local
 458 spatio-temporal structural information from the original output, a residual path is
 459 incorporated and integrated via linear fusion. The implementation is as shown in
 460 Eq. 15 to 16:

$$\mathbf{Z}_4 = \delta(\text{Conv2D}(\text{Linear}(\mathbf{I}_{\text{input}}), \mathbf{W}_{\text{conv}})) \quad (15)$$

461

$$\mathbf{Z}_5 = \text{Linear}(\mathbf{Z}_3 \oplus \mathbf{Z}_4) \quad (16)$$

462 here, δ denotes the SiLU activation function, and $\oplus$ represents the concatenation
463 operation.

464 Subsequently, further feature processing is performed using CNN, MaxPooling,
465 and BatchNormalization to strengthen the model's perception of spatial and temporal
466 variations:

$$\mathbf{Z}_6 = \text{Conv2D}(\mathbf{Z}_5, \mathbf{W}_{cnn}) \quad (17)$$

467

$$\mathbf{Z}_7 = \text{MaxPooling2D}(\mathbf{Z}_6) \quad (18)$$

468

$$\mathbf{Z}_8 = \text{BatchNorm}(\mathbf{Z}_7) \quad (19)$$

469 In the decoder, after spatio-temporal features have been extracted from the sea ice
470 data, the next step is to decode and reconstruct these features to generate the final
471 sea ice concentration prediction map. The feature maps are restored to their spatial
472 dimensions through Conv2D operations:

$$\mathbf{Q}_1 = \text{Mamba}(\mathbf{Q}_{input}) \quad (20)$$

473 The Mamba operation is defined as:

$$\text{Mamba}(\mathbf{Q}_{input}) = \text{LN}(\delta(\text{LN}(\mathbf{Q}_{input})) + \text{SSM}(\delta(\text{Conv}(\text{LN}(\mathbf{Q}_{input})))))) \quad (21)$$

474

$$\mathbf{Q}_2 = \text{Conv2D}(\text{CNN}(\mathbf{Q}_1)) \quad (22)$$

475 In these expressions, SSM refers to the state-space model, $\mathbf{Q}_{input}$ denotes the input
476 to the STDB module, LN represents layer normalization, σ is the *SiLU* activation
477 function, $\mathbf{Q}_1$ is the output of the Mamba block, and $\mathbf{Q}_2$ is the final output of the
478 STDB module.

3.3 Multi-dimensional attention mechanism

In the field of sea ice prediction, accurately capturing complex spatiotemporal patterns in the marine environment is crucial for improving forecast accuracy. Sea ice distribution and changes are influenced by multiple factors, including ocean temperature and atmospheric conditions such as wind speed. These factors interact across varying temporal and spatial scales, forming highly complex spatiotemporal data patterns. Therefore, we designed an attention mechanism to fully capture subtle variations and key features within the data, as shown in Fig. 4. Within the sea ice prediction model, the channel attention mechanism (CAtn) dynamically calibrates the contribution levels of multi-source feature channels, such as specific ocean temperature layers, effectively enhancing the model's weighting of critical features while suppressing interference from irrelevant characteristics. The spatial attention mechanism (SAtn) focuses on key regions of sea ice change, such as sea ice edge zones or specific areas significantly influenced by ocean currents, thereby strengthening the model's ability to resolve regional features.

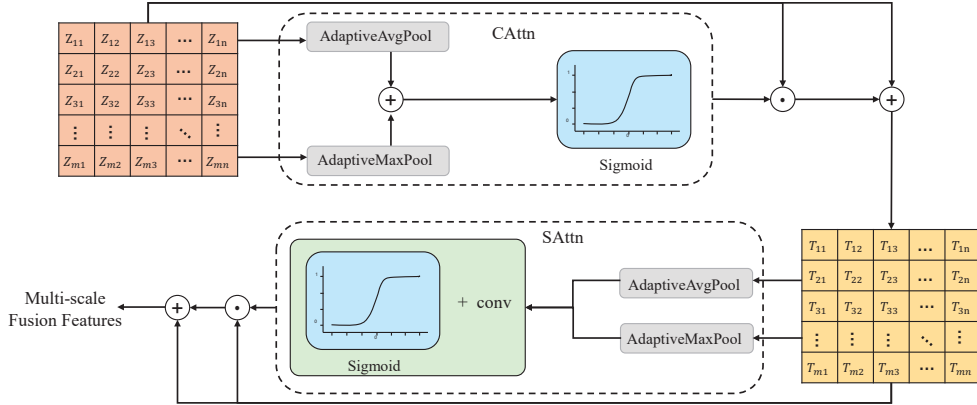


Fig. 4 Schematic diagram of multi-dimensional attention mechanism

494 The integration of this dual attention mechanism enables the model to more
 495 accurately capture the spatiotemporal characteristics of sea ice variation, thereby
 496 improving prediction accuracy. The specific implementation is as shown in Eq. 23 to
 497 24:

$$498 \quad \mathbf{T}_o(\mathbf{Z}) = \mathbf{Z} \odot CAttn(\mathbf{Z}) + \mathbf{Z} \quad (23)$$

$$Attn(\mathbf{T}_o) = \mathbf{T}_o \odot SAttn(\mathbf{T}_o) + \mathbf{T}_o \quad (24)$$

499 here, $\mathbf{Z}$ is the input feature with shape (B, C, H, W) where B is the batch size, C is
 500 the number of channels, and H and W are the height and width of the feature map,
 501 respectively. $\mathbf{T}_o$ denotes the feature map after channel-wise weighting, and $CAttn$ and
 502 $SAttn$ represent the channel attention and spatial attention modules, respectively.

503 The channel attention mechanism dynamically adjusts the importance of different
 504 channels by assigning varying weights to each channel. This enhances the model's
 505 sensitivity to informative input channels, allowing it to focus on more useful features
 506 while suppressing irrelevant ones. The channel attention is computed as shown in
 507 Eq. 25 to 27:

$$508 \quad Avg_{fc} = FC(AdaptiveAvgPool(\mathbf{Z})) \quad (25)$$

$$509 \quad Max_{fc} = FC(AdaptiveMaxPool(\mathbf{Z})) \quad (26)$$

$$CAttn(\mathbf{Z}) = \sigma(FC(Avg_{fc}(\mathbf{Z})) + FC(Max_{fc}(\mathbf{Z}))) \quad (27)$$

510 here $AdaptiveAvgPool$ and $AdaptiveMaxPool$ represent adaptive average pooling
 511 and adaptive max pooling operations, respectively. These operations similarly pool
 512 feature maps to the dimension $(C, 1, 1)$, FC represents a fully connected layer, and σ
 513 is the Sigmoid activation function.

514 The spatial attention mechanism focuses on spatial location information in sea ice
 515 data. By identifying and emphasizing key regions where sea ice is present, this mod-
 516 ule more effectively captures critical features of sea ice changes from highly complex
 517 spatiotemporal data patterns. The spatial attention is implemented as shown in Eq. 28:

$$SAttn(\mathbf{T}_o) = \sigma \left(Conv \left([Avg_{fc}(\mathbf{T}_o), Max_{fc}(\mathbf{T}_o)] \right) \right) \quad (28)$$

518 here, Avg_{fc} represents calculating the average value along the channel size C to
 519 obtain shape $(1, H, W)$; Max_{fc} represents finding the maximum value along the chan-
 520 nel dimension C , which also produces the shape $(1, H, W)$. $[Avg_{fc}(\mathbf{T}_o), Max_{fc}(\mathbf{T}_o)]$
 521 represents the shape $(2, H, W)$ generated by connecting two feature maps along the
 522 channel dimension. $Conv$ represents the 2D convolution operation applied to cascaded
 523 feature maps, outputting feature maps with shapes of $(1, H, W)$. σ is the Sigmoid acti-
 524 vation function used to normalize the output feature map of convolution to the range
 525 of $[0, 1]$.

526 4 Experiments and discussions

527 4.1 Experimental settings

528 4.1.1 Datasets

529 Due to the complex nonlinear interactions between atmospheric-oceanic boundary
 530 dynamics and SIC, we integrate satellite-derived observational records from the
 531 National Snow and Ice Data Center (NSIDC) with atmospheric and oceanic reanaly-
 532 sis from ERA5 across the 1979–2021 period to construct a spatiotemporal predictor
 533 dataset.

534 **NSIDC Sea Ice Concentration Data**, we utilize the NSIDC Climate
 535 Data Record of Passive Microwave Sea Ice Concentration ([https://nsidc.org/data/](https://nsidc.org/data/explore-data)
 536 [explore-data](https://nsidc.org/data/explore-data)). The dataset provides daily SIC at a nominal spatial resolution of

537 25 km $\times$ 25 km projected onto the NSIDC Polar Stereographic Northern Hemisphere
 538 grid (304 $\times$ 448 pixels). Land areas and missing observations are masked out using
 539 standard NSIDC land-sea masks.

540 **ERA5 Reanalysis Predictor Variables**, atmospheric and oceanic variables
 541 are extracted from the ECMWF ERA5 global reanalysis at a spatial resolution of
 542 $0.25^\circ \times 0.25^\circ$ (<https://cds.climate.copernicus.eu>).

543 The selection of environmental driving variables is guided by the thermodynamic
 544 and dynamic mechanisms governing sea ice evolution. The sea ice prediction vari-
 545 ables used are detailed in Table 1. Sea surface temperature governs lateral and basal
 546 thermodynamic melting by tracking upper-ocean heat storage; downward longwave
 547 radiation serves as a dominant surface energy balance component, with enhanced
 548 downward longwave flux intensifying surface thermal loading and accelerating melting
 549 during seasonal transitions; rain rate alters surface albedo through liquid precipita-
 550 tion and facilitates pond formation, thereby triggering the melt-albedo feedback; and
 551 snow rate controls the accumulation of insulating snow cover, which modulates winter
 552 thermodynamic ice growth and reflects solar radiation in spring.

Table 1 Characteristics of sea ice prediction variables

Variable	Source	Temporal Resolution	Spatial Resolution	Units
Sea Ice Concentration	NSIDC	Daily	25 km	%
Longwave Radiation	ERA5	Hourly	0.25°	W/m ²
Rain Rate	ERA5	Daily	0.25°	mm/d
Snow Rate	ERA5	Daily	0.25°	mm/d
Sea Surface Temperature	ERA5	Daily	0.25°	K

553 Due to significant differences in spatial resolution and temporal scale between
 554 ERA5 data and NSIDC data, systematic preprocessing is required to generate a unified
 555 format tensor suitable for modeling.

556 The spatial dimension of ERA5 data is defined as a latitude-longitude grid
 557 $D_{ERA5} \in \mathbb{R}^{L \times M \times F}$, where L and M correspond to the latitude and longitude dimen-
 558 sions, respectively, and F is the number of features. The spatial dimension of NSIDC
 559 sea ice concentration data is defined as F , where H and W denote the number of
 560 pixels in the latitude and longitude directions of the projection grid, respectively, and
 561 the feature dimension is 1, representing sea ice concentration. Bicubic interpolation is
 562 employed to map the ERA5 dataset's latitude-longitude grid onto the NSIDC polar
 563 projection grid, as shown in Eq. 29:

$$\hat{d}(h, w, f) = \sum_{i=0}^1 \sum_{j=0}^1 w_{i,j} \cdot d_{ERA5}(l+i, m+j, f) \quad (29)$$

564 where $\hat{d}(h, w, f)$ is the interpolated value of feature f at NSIDC grid point (h, w) ,
 565 with $f \in [1, F]$ representing the feature index, $w_{i,j}$ is the interpolation weight,
 566 calculated as the inverse of the distance between the NSIDC grid point (h, w) and the
 567 ERA5 nearest grid points, satisfying $\sum_{i=0}^1 \sum_{j=0}^1 w_{i,j} = 1$, $(l+i, m+j, f)$ denotes the
 568 four nearest grid points (l, m) in the ERA5 dataset ($l \in L, m \in M$), and $d_{ERA5}(l+i,$
 569 $m+j, f)$ represents the original value of the ERA5 dataset at $(l+i, m+j, f)$. After
 570 resampling, the ERA5 data aligned with the NSIDC spatial resolution is denoted as
 571 $\hat{D}_{ERA5} \in \mathbb{R}^{L \times M \times F}$

572 ERA5 variables such as longwave radiation are hourly data, requiring aggregation
 573 to a daily scale to match NSIDC's daily sea ice concentration data. Let the hourly
 574 data for a feature f be $d_{hourly}(t, h, w, f)$ (where $t \in [1, T_{day}]$ represents the hourly
 575 index for the day). The daily aggregated value is expressed as shown in Eq. 30:

$$d_{daily}(d, h, w, f) = \frac{1}{24} \sum_{t=1}^{24} d_{hourly}(t, h, w, f) \quad (30)$$

where $d_{hourly}(d, h, w, f)$ is the mean value of the 24-hour period on day $d_{daily}(d, h, w, f)$, and D is the total number of days. Finally, merging the NSIDC daily SIC data with the ERA5 daily resampled data yields $D_{daily} \in \mathbb{R}^{D \times H \times (F+1)}$.

4.1.2 Evaluation metrics

To comprehensively evaluate the predictive performance of the STICEnet model, we employed $RMSE$, MAE , and R^2 score as evaluation metrics. Since it is a spatio-temporal dataset corresponding to latitude and longitude values, the $RMSE$ and MAE metrics were customized using the following formula for model evaluation:

$$RMSE_{SIC} = \sqrt{\frac{\sum_u \sum_v (Y[u, v] - \hat{Y}[u, v])^2}{N}} \quad (31)$$

$$MAE_{SIC} = \frac{\sum_u \sum_v |Y[u, v] - \hat{Y}[u, v]|}{N} \quad (32)$$

here, u and v correspond to latitude and longitude indices, Y represents the true values, $\hat{Y}$ denotes the predicted SIC values, and N is the total number of test samples. Both $RMSE$ and MAE quantify prediction errors. $RMSE$ is more sensitive to larger errors due to the squared term, while MAE provides a more stable measure of the average deviation.

$RMSE$ and MAE evaluate the numerical prediction accuracy of the model, while R^2 more precisely assesses the model's ability to capture the spatiotemporal variation patterns of sea ice concentration, as shown in the following equation:

$$R^2 = 1 - \frac{\sum_u \sum_v (Y[u, v] - \hat{Y}[u, v])^2}{\sum_u \sum_v (Y[u, v] - \bar{Y})^2} \quad (33)$$

where $\bar{Y}$ is the mean value of the true SIC over all test samples. A higher R^2 value indicates better model performance.

4.1.3 Experimental setup

The STICEnet model was trained using the Keras Functional API with the TensorFlow deep learning framework, containing approximately 148,000 trainable parameters. It employed the Adam optimizer with root mean square error (RMSE) loss, trained over 100 epochs using early stopping with a learning rate of 0.0001. The training set utilized data from 408 months spanning 1979 to 2015, while the test set employed data from 96 months covering 2016 to 2018.

4.2 Comparative experiment

To validate the effectiveness of the proposed model, comparative experiments were conducted against several baseline models, including CNN, ConvLSTM, Multi-task ConvLSTM, IceNet, and MT-IceNet. These models were proposed by [Purwono et al. \(2022\)](#); [Li et al. \(2021\)](#); [Kim et al. \(2021\)](#); [Andersson et al. \(2021\)](#); [Ali and Wang \(2022\)](#), respectively. Evaluations across $RMSE$, MAE , and R^2 are summarized in Tables 2, 3, and 4.

Table 2 $RMSE$ (%) scores of SIC predictions across different models

Model	Lead 1 month	Lead 2 month	Lead 3 month	Lead 4 month	Lead 5 month	Lead 6 month
CNN	11.34	11.75	12.51	12.71	13.03	12.72
ConvLSTM	9.12	9.45	11.00	11.07	10.26	9.89
Multi-task ConvLSTM	11.73	12.02	12.61	15.79	13.12	12.86
IceNet	13.07	17.42	17.14	18.43	21.37	18.20
MT-IceNet	5.50	6.73	7.61	7.96	7.87	7.77
Ours	5.36	6.46	7.45	7.73	7.64	7.51

As shown in Table 2, Table 3, and Table 4, STICEnet consistently achieves the lowest $RMSE$ across all prediction lead times ranging from 1 to 6 months.

Table 3 *MAE* (%) scores for SIC predictions across different models

Model	Lead 1 month	Lead 2 month	Lead 3 month	Lead 4 month	Lead 5 month	Lead 6 month
CNN	3.163	3.357	3.470	3.703	3.655	4.142
ConvLSTM	2.569	2.838	3.178	3.241	3.041	3.219
Multi-task ConvLSTM	3.665	3.622	3.923	5.591	4.305	4.267
IceNet	8.564	8.749	8.448	9.536	12.277	9.157
MT-IceNet	1.313	1.983	1.962	2.164	2.154	1.967
Ours	1.236	1.679	1.863	2.024	1.983	1.928

Table 4 R^2 scores for SIC predictions across different models

Model	Lead 1 month	Lead 2 month	Lead 3 month	Lead 4 month	Lead 5 month	Lead 6 month
CNN	0.838	0.826	0.802	0.796	0.786	0.796
ConvLSTM	0.892	0.885	0.839	0.840	0.860	0.870
Multi-task ConvLSTM	0.823	0.813	0.793	0.673	0.773	0.781
IceNet	0.777	0.604	0.616	0.556	0.403	0.567
MT-IceNet	0.958	0.929	0.919	0.911	0.913	0.915
Ours	0.968	0.937	0.929	0.942	0.921	0.925

In the short-range forecasting phase (Leads 1–2), STICEnet demonstrates superior precision with an *RMSE* of 5.36% and an *MAE* of 1.236% at Lead 1, outperforming MT-IceNet (5.50% *RMSE*, 1.313% *MAE*) and surpassing standard ConvLSTM (9.12% *RMSE*) by over 41%. This immediate advantage is primarily driven by the TCCE module, which strictly enforces unidirectional causality to prevent reverse temporal leakage from future time steps during rapid freeze-thaw state transitions. Concurrently, the multi-dimensional attention mechanism adaptively calibrates high-variance atmospheric fluxes (such as downward longwave radiation and sea surface temperature), preventing early error propagation in dynamically vulnerable marginal ice zones.

In extended multi-lead forecasting (Leads 3–6), recurrent architectures suffer from cumulative error compounding, with ConvLSTM and Multi-task ConvLSTM exhibiting *RMSE* values reaching 11.07% and 15.79%, respectively. Similarly, IceNet

experiences substantial correlation degradation (R^2 dropping to 0.403–0.567). In contrast, STICEnet exhibits high predictive stability, maintaining an $RMSE$ of 7.51%, an MAE of 1.928%, and an R^2 of 0.925 at Lead 6. This long-horizon robustness stems from the state-space dynamic modeling within the MSFED module, which efficiently preserves continuous global memory across extended sequence lengths without incurring recursive gradient decay. Furthermore, the TTCD mechanism preserves structural temporal continuity during multi-scale reconstruction, effectively avoiding prediction discontinuities over long-term seasonal evolutions.

4.3 STICEnet prediction results analysis

To evaluate the generalization capability and physical responsiveness of STICEnet under non-stationary Arctic climate conditions, multi-horizon forecasts across both standard evaluation intervals and the completely unseen post-hoc period (January 2019 to December 2021) were comprehensively analyzed. This post-hoc period represents an extreme low-ice regime characterized by accelerated multi-year ice loss and amplified thermodynamic volatility.

As shown in Fig. 5, we plotted the predicted SIE values as a time series across multiple lead periods to analyze the impact of seasonal fluctuations and long-term trends on prediction accuracy. Specifically, Lead month 1 through Lead month 6 represent predictions for the current month generated using historical data from one to six months prior, respectively. The multi-lead forecast trajectories produced by STICEnet closely track the observational SIE trajectories throughout the multi-year cycle, reliably capturing both the seasonal inflection points and the multi-scale amplitude envelope.

For short lead times (Leads 1–2), the predicted curves exhibit exceptional fidelity to the observational benchmark, accurately synchronizing with both the winter maximum expansion and the late-summer minimum retreat, with peaks and troughs aligning closely with observed trends. This tight coupling is primarily attributed to the TCCE

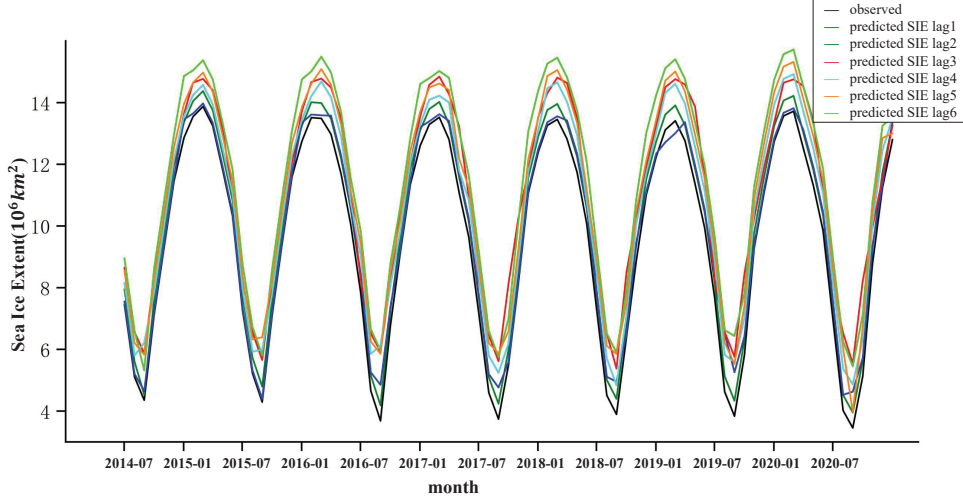


Fig. 5 Model-specific sea ice extent prediction curves for different lead months

module, which enforces strict unidirectional causal constraints, thereby eliminating temporal leakage and maintaining physical consistency during rapid seasonal phase transitions. These results demonstrate the model's ability to effectively capture sea ice dynamics in short-term forecasts.

As the forecast horizon extends to Lead 5 and Lead 6, prediction accuracy decreases, and minor amplitude offsets emerge near the annual extrema. Nevertheless, the global phase alignment and the monotonic rates of ice advance and retreat remain intact, and the error margins within ascending or descending intervals stay small relative to observations. This indicates that the model still effectively captures sea ice dynamics in long-term forecasting. Notably, during the 2016–2017 anomaly period, long-lead predictions exhibited localized positive deviations. This discrepancy corresponds to the super El Niño event and associated anomalous atmospheric wave trains that drove intense poleward moisture and heat fluxes into the central Arctic Basin. Such external atmospheric perturbations temporarily disrupted local thermodynamic equilibrium, illustrating the sensitivity of long-range seasonal forecasting to extreme non-local climatic forcings.

665 To examine the model’s capability in resolving seasonal transitions and periodic
666 fluctuations, hindcasts at a 3-month lead time were systematically evaluated against
667 ground-truth satellite observations. Arctic SIE exhibits strong seasonal cycles governed
668 by coupled thermodynamic and dynamic processes, where resolving seasonal turn-
669 ing points provides critical insights into polar air-sea-ice interactions and large-scale
670 atmospheric circulation anomalies.

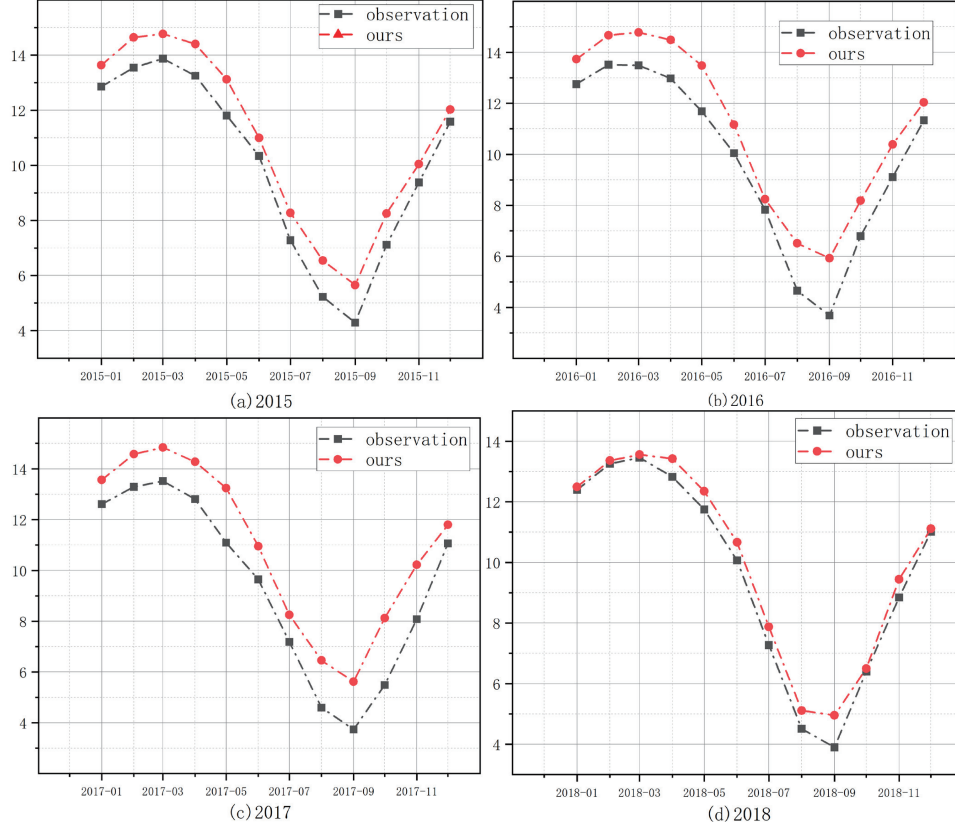


Fig. 6 Monthly sea ice extent forecast curves for 2015-2018

671 As illustrated in Fig. 6, the sea ice extent displays distinct periodic behavior across
672 consecutive annual cycles, and the STICNet predictions remain largely consistent
673 with observations throughout most of the period.

674 During the winter expansion phase (January–March, Fig. 6(a)–(d)), sea ice reaches
675 its annual maximum extent. STICEnet reliably reproduces these peaks, confirming its
676 capability to model basal thermodynamic ice growth and cold-season consolidation
677 across the central Arctic Basin. The slight positive offsets observed in winter 2015,
678 2016, and 2017 correspond to episodic winter warm air intrusions across the Barents-
679 Kara Seas, where localized heat pulses hindered complete freeze-up.

680 During the spring-to-summer transition (April–September), rising air tempera-
681 tures and intense shortwave/longwave radiation trigger surface melting, melt-pond
682 formation, and positive ice-albedo feedbacks. STICEnet captures this steep downward
683 trajectory with minimal phase lag. Minor deviations during the 2016 and 2017 melt
684 seasons reflect high stochasticity in atmospheric circulation patterns. At the September
685 seasonal minimum, the model closely bounds the retreat boundary.

686 During the autumn refreezing stage (October–December), rapid thermal radiation
687 loss drives ice expansion across the marginal ice zones. The predicted trajectories cap-
688 ture this steep congelation phase without the temporal lag commonly encountered in
689 traditional recurrent baselines. This seasonal fidelity demonstrates that the unidirec-
690 tional constraints from TCCE and the multi-variable attention weighting on downward
691 longwave flux and SST allow STICEnet to adaptively track seasonal turning points.

692 Between 2019 and 2021, Arctic sea ice coverage and thickness continued to decline,
693 accompanied by a sharp reduction in multi-year ice proportion—a trend largely driven
694 by Arctic amplification and closely linked to human activities. To assess the out-of-
695 distribution generalization capability of STICEnet under such non-stationary extreme
696 climatic conditions, the model’s multi-month predictions were evaluated against
697 satellite observations across this unseen post-hoc period, as depicted in Fig. 7.

698 As shown in Fig. 7, the forecasted trajectory closely synchronizes with the
699 observed annual cycle across the entire 2019–2021 sequence, capturing both the

700 rapid spring-summer retreat gradients and the subsequent autumn-winter congela-
 701 tion slopes. During the winter maximum periods (January–March of 2019, 2020, and
 702 2021), the predicted peaks align tightly with the observed timing, exhibiting only a
 703 slight positive offset (peaking near $15.5\text{--}15.7 \times 10^6 \text{ km}^2$ compared to the observed
 704 $14.7\text{--}15.0 \times 10^6 \text{ km}^2$). During the spring transition phases (e.g., March to June in
 705 both 2019 and 2020), the model accurately reproduces the steep downward trajec-
 706 tory and matches the observational curves at the mid-melt transition points (around
 707 April–May).

708 During the summer minimum periods (July to September in 2019 and 2020),
 709 the observed sea ice extent dropped to extreme historical minima of approximately
 710 $4.5 \times 10^6 \text{ km}^2$ (2019) and $4.1 \times 10^6 \text{ km}^2$ (2020). While STICEnet successfully cap-
 711 tured the overall trough profile, it exhibited a noticeable positive deviation, leveling off
 712 around $6.2\text{--}6.5 \times 10^6 \text{ km}^2$ and initiating the refreezing upturn slightly earlier than the
 713 ground-truth observations. This discrepancy is primarily attributed to unprecedented
 714 anomalous heatwaves over the Siberian Arctic and intensified positive ice-albedo feed-
 715 backs in the marginal seas (such as the Laptev and East Siberian Seas), which induced
 716 severe sub-grid localized melting beyond standard historical training distributions.

717 Despite these extreme thermodynamic perturbations, STICEnet maintained high
 718 phase fidelity without exhibiting phase lag or catastrophic error accumulation dur-
 719 ing the multi-year cycle. The state-space sequence modeling in the MSFED module
 720 effectively preserved long-term temporal continuity, while the multi-dimensional atten-
 721 tion mechanism and TCCE causal constraints ensured robust boundary stability and
 722 rapid re-synchronization with ground-truth observations during the autumn refreezing
 723 phases (October–December).

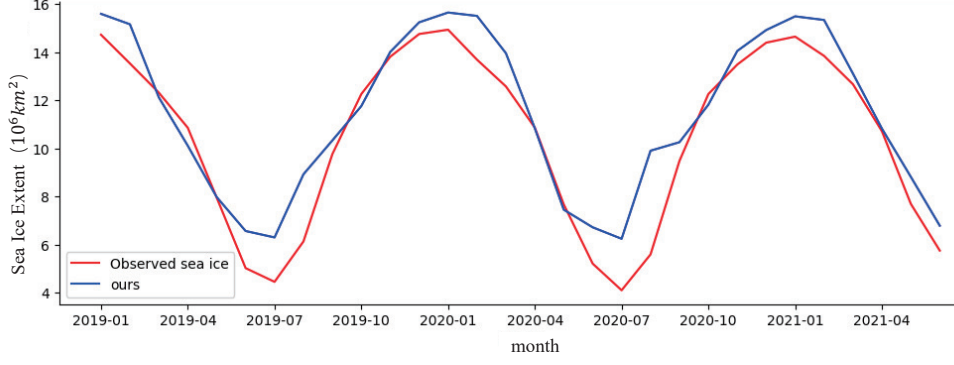


Fig. 7 2019-2021 sea ice extent forecast curve

4.4 STICEnet visual analytics

To evaluate the spatial fidelity, morphological coherence, and ice edge boundary delineation of STICEnet across seasonal regimes and multi-lead forecast horizons, 2D spatial distribution fields of predicted sea ice concentration were analyzed. Each pixel value represents the continuous sea ice area fraction within the $[0\%, 100\%]$ range projected onto the $25 \text{ km} \times 25 \text{ km}$ NSIDC polar stereographic grid.

Spatial evaluations were conducted across four climatologically pivotal transitional months in 2015: the annual maximum extent (March), the onset of rapid spring melt (June), the summer minimum extent (September), and the rapid autumnal freeze-up (December). Fig. 8 compares satellite ground-truth observations against STICEnet predictions at 1-month, 3-month, and 6-month lead times. Each row corresponds to a single target month, presenting the ground-truth observation alongside the respective multi-lead forecasts. In the spatial colormap, white denotes consolidated sea ice with high concentration ($> 80\%$), intermediate light-blue tones represent diffuse marginal ice zones (MIZ, $15\% - 80\%$), and dark blue corresponds to open water and masked landmasses.

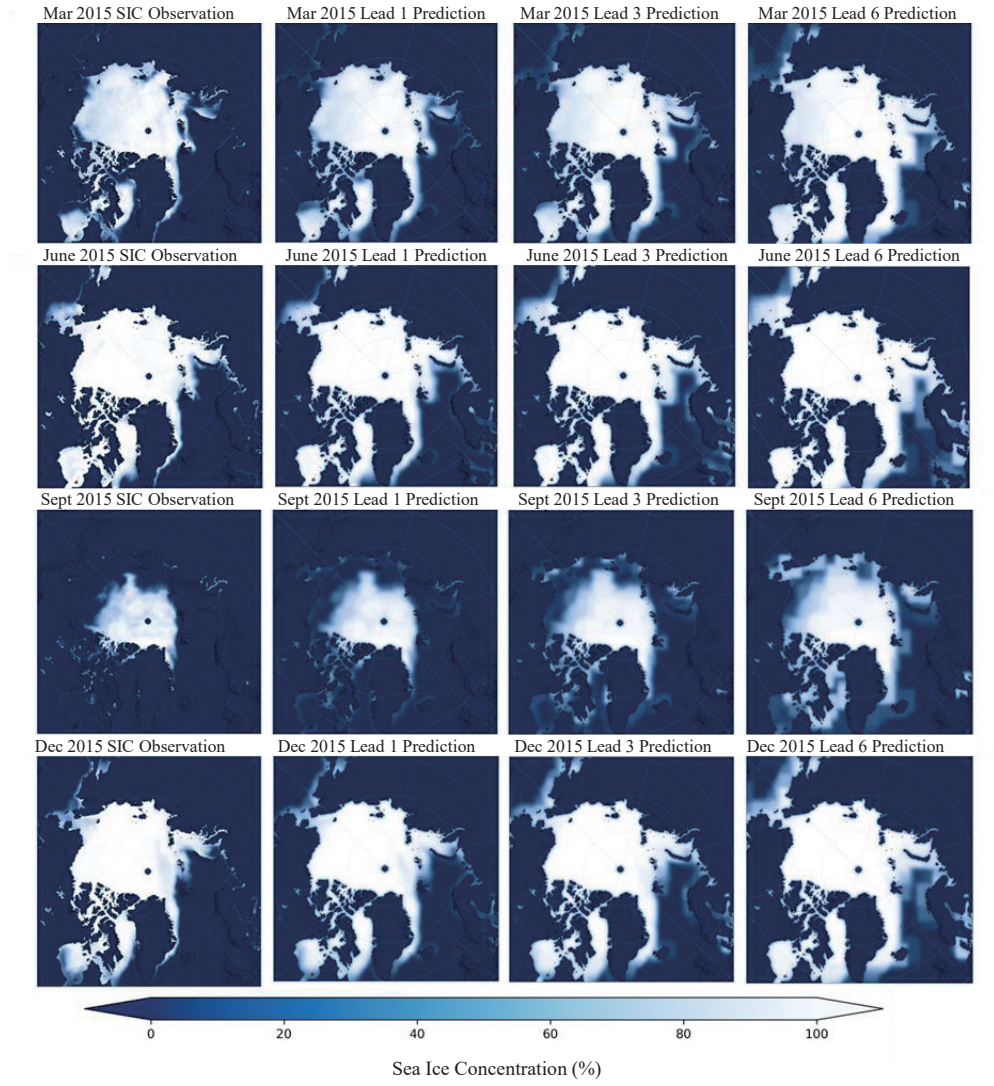


Fig. 8 Visualization of STICEnet predicted sea ice concentration for different lead months

As shown in Fig. 8, STICEnet demonstrates robust spatial continuity, sharp boundary delineation, and stable multi-year ice pack preservation across diverse seasonal stages:

During the winter maximum (March 2015) and freeze-up (December 2015), the multi-lead forecasts accurately reproduce the spatial coverage across the central Arctic

Basin and peripheral seas. The transpolar ice pack and high-concentration regions ($> 90\%$) match observational fields across all lead times. The predicted 15% ice extent contour tightly aligns with observational boundaries at Lead 1 and Lead 3. At Lead 6, the model exhibits a mild spatial diffusion along the outer marginal boundaries, appearing as a slightly widened transitional light-blue buffer; however, the overall regional topological structure remains physically consistent.

During the active melting and retreat regimes (June and September 2015), where thermodynamic and dynamic volatility is highest, STICEnet captures the non-uniform spatial retreat patterns. In June 2015, the model resolves the asymmetric melting dynamics between the Pacific sector and the Atlantic sector. In September 2015, when Arctic sea ice reaches its annual minimum, STICEnet reproduces the spatial configuration of the perennial ice core off the Canadian Arctic Archipelago and northern Greenland, while retaining open-water zones across the Siberian seas.

Crucially, throughout the multi-lead decoding sequence, the predicted spatial fields maintain smooth gradients across marginal ice zones without displaying blocky checkerboard artifacts or discontinuous grid distortions. This structural stability is enabled by the combination of bilinear feature interpolation with convolutional refinement in the decoding pathway, the Mamba-based MSFED module’s continuous global sequence memory, and the multi-dimensional attention mechanism’s regional feature recalibration.

4.5 Ablation studies

To validate the effectiveness of the proposed sea ice prediction architecture, we focus particularly on changes in prediction accuracy across representative forecast horizons (Lead 1, 3, and 6 months) with the incremental integration of core modules. The MT-IceNet model serves as the Base model. By sequentially incorporating the TEDCM, the MSFED, and the Attn, and using $RMSE$, R^2 and MAE as quantitative metrics, we

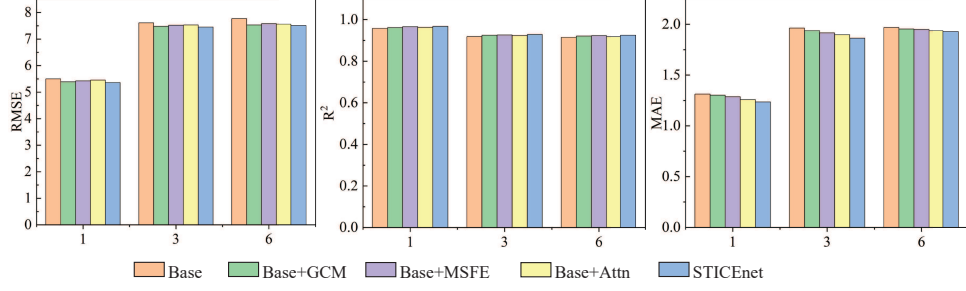


Fig. 9 Model core component ablation experiment results

771 evaluate the contribution of each module combination to prediction performance. The
 772 ablation results evaluated across $RMSE$, R^2 , and MAE are summarized in Table 5
 773 and Fig. 9.

Table 5 Results of sea ice concentration prediction ablation experiments

Method	Lead 1 month			Lead 3 month			Lead 6 month		
	$RMSE$ (%)	R^2	MAE (%)	$RMSE$ (%)	R^2	MAE (%)	$RMSE$ (%)	R^2	MAE (%)
Base	5.50	0.958	1.313	7.61	0.919	1.962	7.77	0.915	1.967
Base+TEDCM	5.39	0.962	1.302	7.48	0.925	1.938	7.53	0.921	1.953
Base+MSFED	5.42	0.966	1.286	7.52	0.926	1.915	7.58	0.923	1.948
Base+Attn	5.45	0.963	1.257	7.53	0.924	1.897	7.56	0.918	1.936
STICEnet	5.36	0.968	1.236	7.45	0.929	1.863	7.51	0.925	1.928

774 As indicated in Table 5, integrating each individual component yields consistent
 775 performance improvements over the baseline across all lead times, confirming their
 776 specific structural advantages in capturing sea ice evolution.

777 The integration of the temporal coordination mechanism (Base+TEDCM) yields
 778 the most pronounced reduction in $RMSE$, lowering the error from 5.50%, 7.61%, and
 779 7.77% in the baseline to 5.39%, 7.48%, and 7.53% for 1-month, 3-month, and 6-month
 780 leads, respectively. This substantial gain demonstrates the critical role of the TCCE
 781 module in enforcing strict unidirectional causal constraints, which prevents future
 782 temporal leakage during feature extraction. By ensuring physical forward-looking

783 consistency, TEDCM suppresses the phase distortion and spurious cross-temporal cor-
784 relations common in conventional bidirectional convolutions, particularly during rapid
785 spring melt onsets.

786 Incorporating the state-space module (Base+MSFED) primarily enhances the
787 correlation metric R^2 , elevating it to 0.966, 0.926, and 0.923 across the three fore-
788 cast horizons. This improvement highlights the capability of Mamba-based sequence
789 modeling in capturing non-stationary long-range dependencies and multi-scale tem-
790 poral dynamics. Unlike recurrent architectures that suffer from gradient attenuation,
791 MSFED maintains continuous hidden state trajectories over long sequence lengths,
792 allowing the network to retain persistent thermodynamic memory across seasonal
793 transition boundaries.

794 The addition of the multi-dimensional attention mechanism (Base+Attn) achieves
795 notable improvements in MAE , reducing the error to 1.257% at Lead 1 and 1.897%
796 at Lead 3. By dynamically recalibrating the contribution of multi-source atmospheric-
797 oceanic driving channels (e.g., downward longwave radiation and sea surface temper-
798 ature) and focusing spatially on vulnerable marginal ice zones, the attention module
799 mitigates localized prediction biases and enhances boundary sharpness.

800 When all components are jointly coupled in the complete STICEnet architecture,
801 the model attains the best overall performance across all evaluated metrics. Compared
802 to the baseline, STICEnet achieves net $RMSE$ reductions of 0.14%, 0.16%, and 0.26%,
803 alongside corresponding MAE reductions of 0.077%, 0.099%, and 0.039% at 1-month,
804 3-month, and 6-month lead times, respectively. The peak R^2 scores (0.968, 0.929, and
805 0.925) confirm the complementary synergy among causal temporal constraints, state-
806 space sequential representation, and spatial-channel feature recalibration in multi-step
807 Arctic sea ice concentration forecasting.

808 5 Conclusion

809 In this work, we propose STICEnet, a sequence-modeling-based U-Net architecture
810 for sea ice concentration prediction, aiming to enhance the model’s ability to cap-
811 ture multi-timescale characteristics of sea ice dynamics. First, addressing temporal
812 modeling challenges, the model integrates time-causal convolutions with transposed
813 convolutions to establish a physical-time-aligned encoding-decoding mechanism, effec-
814 tively preventing forward information leakage. Second, the designed multi-scale
815 spatio-temporal feature encoding-decoding structure enhances prediction accuracy in
816 complex dynamic scenarios by integrating multi-scale feature information. Addition-
817 ally, multidimensional attention mechanisms are integrated into skip connections to
818 adaptively highlight key feature channels and spatial locations, optimizing the feature
819 fusion process. Through multi-source data fusion of NSIDC sea ice concentration data
820 and ERA5 reanalysis products, we systematically validated STICEnet’s capability to
821 capture complex nonlinear relationships between atmospheric-oceanic drivers and sea
822 ice dynamics. Experimental results demonstrate that STICEnet exhibits outstanding
823 performance in medium-to-short-term forecasts spanning 1 to 6 months, outperform-
824 ing existing models in terms of $RMSE$, MAE and the R^2 metrics. However, the model
825 inadequately captures interannual sea ice decay patterns and anomalous responses to
826 extreme climate forcings (e.g., strong El Niño events), primarily due to its limited mod-
827 eling capacity for slow variables and nonlinear cumulative effects within the climate
828 system. Based on these findings, future research will focus on two key directions: First,
829 establishing an sea ice anomaly-meteorological anomaly coupled prediction framework
830 to leverage SIC forecasts for extreme weather early warning. Second, incorporating
831 more expressive time-series modeling modules to enhance the model’s adaptability
832 and generalization capabilities regarding long-term climate background information.

833 **Statements and declarations**

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837 **Competing interests**

838 The authors declare that they have no known competing financial interests or personal
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840 **Author contributions**

841 All authors contributed to the study conception and design. Guoxiang Tong
842 contributed to conceptualization, methodology, formal analysis, investigation, and
843 writing-review and editing. Zeyang Zhang and Wei Shao contributed to conceptu-
844 alization, methodology, software, formal analysis, investigation, visualization, and
845 writing-original draft, review, and editing. Shiliang Wang contributed to conceptu-
846 alization and methodology. Material preparation, data collection, and analysis were
847 performed by Guoxiang Tong, Zeyang Zhang, and Wei Shao. All authors read and
848 approved the final manuscript.

849 **Data availability**

850 The sea ice concentration data used in this study are publicly available from the NSIDC
851 Climate Data Record of Passive Microwave Sea Ice Concentration at <https://nsidc.org/data/explore-data>. The atmospheric and oceanic predictor variables are publicly
852 available from the ECMWF ERA5 global reanalysis at <https://cds.climate.copernicus.eu>. The processed data and analysis code generated in this study are available from
853 the corresponding author on reasonable request.

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